République Algérienne Démocratique et Populaire وزارة التعليم العالي والبحث العلمي Ministère de l'Enseignement Supérieur Et de La Recherche Scientifique Faculté des Sciences et Technologies جامعية غرداييية

Département des Enseignements Communs en Sciences et de la Technologie

قسم التعليم المشترك في العلوم والتكلولوجيا

Université de Ghardaïa

غرداية في : 2025/06/29

#### إذن بالطباعة (مذكرة ماستر)

بعد الاطلاع على التصحيحات المطلوبة على محتوى المذكرة المنجزة من طرف الطلبة التالية أسماؤهم:

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الإذن بطباعة النسخة النهائية لمذكرة ماستر الموسومة بعنوان

#### Direct Solar Heating of Hydration Baths for Dry Dates: Efficiency and Performance Evaluation

مضاء رئيس القسم س التعليم التعليم المشترك ركفي العلق المطلوم والتكنولوجد



الجمهورية الجزائرية الديمقر اطية الشعبية People's Democratic Republic of Algeria وزارة التعليم العالى والبحث العلمي

وزارة التعليم العالي والبحث العلمي Ministry of Higher Education and Scientific Research

جامعة غرداية



Registration N•

University of Ghardaia كلية العلوم والتكنولوجيا

Faculty of Science and Technology

قسم المشترك في العلوم والتكنولوجيا

Department of Common Teaching in Science and Technology End of study thesis, in view of obtaining the diploma Master's Domain: Material Science Field: Energy Physics Specialty: Energy Physics and Renewable energy

Subject

Direct Solar Heating of Hydration Baths for Dry Dates: Efficiency and Performance Evaluation

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**ACADEMIC YEAR 2024/2025** 

### Dedicace

We did not take the simplest beginnings, and we did not reach the ends except by his favor, and we did not achieve the ends except by his grace.

To the one who delivered the message and performed the trust to the Prophet Muhammad, may God bless him and grant him peace

To the one who was endowed by God with prestige and reverence, to the one who taught me to climb the ladder of life with wisdom and patience, I hope that God will have mercy on him, your words are stars that guide me today and tomorrow

My dear father- May God have mercy on him

To my mother and my beloved to the one who overwhelmed me with her tenderness and generosity to the one who taught me how to stand firmly on the ground to the spring of love to the one who put my happiness and comfort on her happiness

To those whom God gave me the grace of their presence in my life to the strong contract who helped me in my research journey My brothers and sisters to everyone who helped me and had a role in completing this study, asking God to reward everyone with the best reward and then to every student who seeks his knowledge to benefit Islam and Muslims with whatever God gave him of knowledge and knowledge.



Without God's blessing, this research would not have been possible, and I pray to the most honorable creature whom God illuminated with his light. After that, I would like to express my sincere gratitude and appreciation to all those who contributed to my support in preparing this research.

First of all, I would like to warmly thank Mr. A. BENSEDDIK for agreeing to supervise my research work. His wise explanations, tremendous help, and his relevant advice and suggestions have been invaluable. His constant presence and support has been a great encouragement to me and has contributed greatly to the success of this project.

I would also like to express my gratitude to Mr. D. DAOUD for his involvement in my project. His indepth knowledge and experience were of great importance to the progress of my work. His availability, patience, and willingness to share his knowledge were invaluable assets that enabled me to develop my skills and achieve my goals.

I would also like to express my gratitude to Khadija Oulad Hajj Youssef, the laboratory engineer, for her constant help and efforts towards me. Her kind presence, technical support, and sound advice were invaluable in helping me conduct the experiments.

My sincere thanks go to my family, who have supported me every step of the way, and my friends, who have been a constant source of inspiration and encouragement

#### Abstract

This study explores the rehydration kinetics of dry dates using a solar water hydration system under real climatic conditions in Ghardaïa. It focuses on evaluating the thermal response of dates in three regions:El Oued, Guerrara, and Beriane, at hydration temperatures ranging from  $39^{\circ}$ C to  $55^{\circ}$ C.

Mathematical modeling of the rehydration process using Peleg, Weibull, and exponential models yielded high coefficients of determination ( $R^2 > 0.95$ ), confirming their suitability for accurately predicting water absorption kinetics. The effective diffusion coefficients varied considerably with temperature, reflecting the combined effects of water viscosity and molecular mobility.

In addition, an artificial neural network (ANN) model was developed and trained using eight days of meteorological data (ambient temperature, solar irradiation, wind speed, and relative humidity) to predict water temperature inside the solar heater. The ANN model demonstrated excellent predictive performance ( $R^2 = 0.968$ ; MAE = 3.140; RMSE = 4.988), with predicted temperatures closely matching measured values. The high accuracy of the ANN model underscores its potential for real-time temperature prediction, enabling better control and management of the solar rehydration process.

Overall, this study emphasizes the critical role of precise temperature management in optimizing the rehydration of dates and highlights the integration of ANN models as powerful tools for enhancing process efficiency and sustainability in arid regions.

**Keywords:** Date rehydration, Kinetics, Rehydration modeling, Diffusion coefficient, Artificial Neural Networks (ANN).

الملخص

تستكشف هذه الدراسة حركيات إعادة ترطيب التمر الجاف باستخدام نظام ترطيب مائي شمسي تحت الظروف المناخية الحقيقية في غرداية. وتركز على تقييم الاستجابة الحرارية للتمور في ثلاثة مناطق : الوادي، القرارة ، وبريان، عند درجات حرارة ترطيب تتراوح بين 39 درجة مئوية و55 درجة مئوية.

أظهرت النمذجة الرياضية لعملية إعادة الترطيب باستخدام نماذج بيليغ وويبول والنموذج الأسي معاملات تحديد عالية (<R 0.95) ، مما يؤكد ملاءمتها للتنبؤ الدقيق بحركيات امتصاص الماء. كما اختلفت معاملات الانتشار الفعالة بشكل كبير باختلاف درجات الحرارة، مما يعكس التأثيرات المشتركة للزوجة المائية والنشاط الجزيئي.

بالإضافة إلى ذلك، تم تطوير نموذج الشبكات العصبية الاصطناعية (ANN) وتدريبه باستخدام بيانات أرصاد جوية لمدة ثمانية أيام (درجة الحرارة المحيطة، الإشعاع الشمسي، سرعة الرياح، والرطوبة النسبية) للتنبؤ بدرجة حرارة الماء داخل سخان المياه الشمسي. أظهر نموذج ANN أداءً تنبؤيًا ممتازًا (RMS = 4.988 + MAE = 3.140 + R<sup>2</sup> = 0.968)، حيث كانت درجات الحرارة المتوقعة متوافقة بشكل وثيق مع القيم المقاسة. تؤكد الدقة العالية لهذا النموذج إمكانيته في التنبؤ بدرجات الحرارة في الوقت الفعلي، مما يتيح تحكمًا وإدارة أفضل لعملية إعادة الترطيب بالطاقة الشمسية.

بشكل عام، تؤكد هذه الدراسة الدور الحاسم لإدارة درجات الحرارة بدقة في تحسين إعادة ترطيب التمور، كما تسلط الضوء على دمج نماذج ANN كأدوات قوية لتعزيز كفاءة واستدامة العمليات في المناطق الجافة.

الكلمات المفتاحية: إعادة ترطيب التمور، الحركيات، نمذجة إعادة الترطيب، معامل الانتشار، الشبكات العصبية الاصطناعية (ANN).

#### Résumé

Cette étude explore la cinétique de réhydratation des dattes sèches en utilisant un système d'hydratation solaire sous les conditions climatiques réelles de Ghardaïa. Elle se concentre sur l'évaluation de la réponse thermique des dattes dans trois régions : El Oued, Guerrara et Beriane , à des températures d'hydratation variant de 39 °C à 55 °C.

La modélisation mathématique du processus de réhydratation, utilisant les modèles de Peleg, de Weibull et exponentiel, a donné des coefficients de détermination élevés ( $R^2 > 0.95$ ), confirmant leur adéquation pour prédire avec précision la cinétique d'absorption d'eau. Les coefficients de diffusion effectifs ont considérablement varié avec la température, reflétant les effets combinés de la viscosité de l'eau et de la mobilité moléculaire.

De plus, un modèle de réseau de neurones artificiels (ANN) a été développé et entraîné à partir de huit jours de données météorologiques (température ambiante, irradiation solaire, vitesse du vent et humidité relative) afin de prédire la température de l'eau à l'intérieur du chauffe-eau solaire. Le modèle ANN a démontré d'excellentes performances prédictives ( $R^2 = 0.968$ ; MAE = 3,140; RMSE = 4,988), les températures prédites étant très proches des valeurs mesurées. La grande précision du modèle ANN souligne son potentiel pour des prévisions en temps réel, permettant un meilleur contrôle et une gestion plus efficace du processus de réhydratation solaire.

Dans l'ensemble, cette étude souligne le rôle essentiel de la gestion précise de la température pour optimiser la réhydratation des dattes et met en évidence l'intégration des modèles ANN comme outils puissants pour améliorer l'efficacité et la durabilité des processus en zones arides.

**Mots-clés :** Réhydratation des dattes, Cinétique, Modélisation de la réhydratation, Coefficient de diffusion, Réseaux de neurones artificiels (ANN).

#### List of Abbreviations

ANNs: Artificial Neuron Networks	
CNNS: Convolutional Neural Networks	
DBNs: Deep Belief Networks	
EES :Electricl Energy Storage	
LHS: Latent Heat Storage	
MES: Mechanical Energy Storage	9
MLP: Multi-Layer Perceptron	
PCM: Phase Change Material	
R <sup>2</sup> :The coefficient	
RBMs: Restricted Boltzman Machines	
RMSE: The Square Root Of The Mean Square Error	
RNNs: Recurrent Neural Networks	
RR: Rehydratation Ratio	
SLP: Single Layer Perceptron	
TES: Thermal Energy Storage	
W (%): Moisture Content Wet Basis in %	
MAE: The Mean Absolute Error	
MR: The Water Content From The experiment	
MSE: The Mean Squared Error	
R <sup>2</sup> : the coefficient of determination	40
X <sup>2</sup> : Reduced chi Square	

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# General Introduction

#### **General Introduction**

Dates are a crucial agricultural product, especially in arid and semi-arid regions, where they play a significant role in both nutrition and the local economy. Rich in essential nutrients such as carbohydrates, fibers, and minerals, dates provide an important source of sustenance and income for communities in these regions. However, after harvesting, dates often undergo drying processes to extend their shelf life, which can result in significant moisture loss, altering their texture and palatability. Therefore, the rehydration of dried dates is a vital postharvest step to restore their softness, improve consumer acceptance, and enhance market value.

Conventional rehydration techniques typically rely on traditional heating methods (such as gas or electricity), which can be energy-intensive, costly, and unsustainable—particularly in remote desert areas with limited access to conventional energy sources. This has prompted researchers and practitioners to explore more sustainable solutions. In this context, solar energy, as a renewable and abundant resource in arid regions, offers a promising and environmentally friendly alternative for date rehydration.

This study investigates the effectiveness of a solar water heating system in rehydrating dried dates under the real climatic conditions of Ghardaïa, focusing on dates in three regions —El Oued, Guerrara, and Beriane collected from local regions. By evaluating the impact of different water temperatures (ranging from 39°C to 55°C) on the physical properties and rehydration kinetics of these dates, this research aims to identify the optimal operational conditions for quality improvement.

Furthermore, mathematical modeling approaches including Peleg, Weibull, and exponential models were employed to describe the rehydration kinetics, offering a robust framework for predicting water uptake behavior. To enhance process control and real-time monitoring, an artificial neural network (ANN) model was also developed, trained on meteorological data (ambient temperature, solar irradiation, wind speed, and relative humidity) to accurately predict water temperature within the solar heater.

By combining renewable energy utilization with advanced data-driven modeling, this research supports the development of efficient, low-carbon, and economically viable postharvest practices that are tailored to the specific conditions of arid and semi-arid regions.

This approach not only contributes to sustainable agriculture but also enhances the socioeconomic resilience of communities dependent on date production.

Thesis Structure

To address these objectives, this master's thesis is organized into four main chapters:

Chapter I: General and Fundamental Concepts: This chapter provides an overview of solar energy utilization in heating water using PCM.

Chapter II: Artificial Neural Network (ANN): This chapter introduces the theoretical foundation and practical implementation of ANN models, detailing their relevance and application in predicting temperature for solar energy systems.

Chapter III: Materials and Methods :This chapter describes the experimental setup, including the solar water heater system, date varieties studied, measurement techniques, and data collection methods.

Chapter IV: Results and Discussion :This chapter presents the experimental results, evaluates the rehydration kinetics using mathematical models, assesses the ANN model's performance, and discusses the implications for sustainable date rehydration practices.

This structured approach ensures a comprehensive analysis of both the physical phenomena and the modeling techniques employed, culminating in practical recommendations for sustainable postharvest practices in date-producing regions.

## Chapter I: General and fundamental concepts

#### I.1 Introduction

The need for appropriate usage and harvesting of renewable energy resources has drawn attention from around the world due to the rapidly increasing issue of the depletion of available non-renewable energy resources. Solar energy is a significant renewable energy source. The use of PCM (phase change materials) has increased recently. Has emerged as a successful method for capturing and storing solar energy for use in solar water heaters[1].

The rehydration process involves reintroducing water into dry products, such as fruits, vegetables or meats, to make them softer and more tender. This step is essential because it allows restoring the softer texture of foods while preserving flavor and nutritional value [2].

**Energy** is the basis of all activities related to nature: plant growth, wind, river flow, waves, falling objects, and so on. In physics, it's the quantity that determines the work a system can do. Energy has many forms: thermal, kinetic, electrical..., and it can be transformed from one type to another[3].

**Renewable energy** is a natural source of energy that is rapidly replenished, making it inexhaustible on the human scale. It is derived from regular or continuous natural phenomena resulting from the interactions of celestial bodies, such as the sun (solar energy), the earth (geothermal energy), and water (hydroelectricity and tidal energy). Renewable energy is divided into six this is another list [4] :\_\_\_

- $\checkmark$  Solar energy.
- $\checkmark$  Wind energy.
- ✓ Hydropower:
- ✓ Biomass.
- $\checkmark$  Geothermal energy.

#### I.2 Solar Thermal Energy

Solar thermal power generation utilizes solar thermal energy to produce electricity, representing one of the most advanced applications of solar technology. The core principle of a solar thermal power system is capturing heat from solar radiation. To achieve this, various concentration techniques are employed to generate medium- to high-temperature heat from sunlight [5].

#### **I.3.Solar Water Heater**

Domestic Solar Water Heater is a robust and reliable system designed to maximize. the use of solar energy, covering 50- 70% of a household's annual hot water needs, with this rate reaching up to 99 % during summer. The system operates through four main stages:

- absorbing solar radiation and converting it into heat via thermal panels,
- transferring the heat to water through a closed circuit operating with natural or forced circulation,
- storing the hot water in a dedicated tank
- Distributing it to points of use with a backup system when needed.

To ensure the system's efficiency and safety, it must be protected from freezing risks in cold areas and damage from overheating in summer. Its various components also require optimization to minimize energy loss and reduce auxiliary energy consumption, making it an ideal solution for a sustainable and economical hot water supply.

#### I.3.1. Classification of Solar Water Heaters:

**I.3.1.1. Monobloc:** The integrated solar water heater combines solar collectors and storage tank into a single compact unit (Figure I.1), making it a practical system with autonomous operation and easy installation that only requires connecting the cold-water supply pipe and linking the hot water outlet. This type represents the most economical option among solar water heaters, explaining its widespread global adoption. However, it has some limitations, primarily heat loss due to the exposure of both the tank and collectors to weather conditions, along with challenges in architectural integration. These characteristics make it particularly suitable for hot climates and summer use.



Figure I.2. The monobloc solar water heater. [6]

#### I.3.1.2. Thermosiphon

The thermosiphon solar water heating system represents a practical and efficient solution that operates on the principle of natural thermal convection, transferring heat from solar collectors to the storage tank without requiring pumps or any mechanical devices, relying solely on temperature differentials. This necessitates positioning the tank above the solar collectors. The system features an integrated design that combines both collectors and a storage tank into a single unit (Figure I.2), making it easy to install and completely self-operating. However, it does have some drawbacks, including significant heat loss and challenges in architectural integration.

The system offers high reliability with minimal failure risk and low maintenance costs, delivering exceptional performance in sunny regions, particularly when receiving over 2,800 annual sunshine hours. Among its key advantages compared to other systems are its electricity independence and absence of moving parts, ensuring longer operational life. Important design considerations include evaluating the roof's load-bearing capacity and carefully planning the angle and orientation of solar collectors to optimize performance, especially during the summer months. This self-contained solution is particularly suitable for areas with abundant sunlight, though frost protection measures may be required in temperate climates. The simple yet effective design makes it an economical choice for residential applications, particularly in rural settings where reliability and low maintenance are prioritized.



Figure I. 3. Thermosiphon solar water heater. [6]

#### I. 3.1.3. Forced Circulation

The solar water heater equipped with a pump and control system is suitable for various configurations, allowing the storage tank to be installed in lower areas such as a basement or at a distance from the solar collectors. However, the cost of this system is generally higher than that of integrated systems due to the additional equipment, such as the circulation pump and control unit.



Figure I.4. The forced-circulation solar water heater. [6]

- ✓ Flat Plate Solar Collector: The role of the solar collector is to absorb as much solar energy as possible while minimizing heat loss through cooling, then transfer this heat to the circulating water, which will be used to heat domestic water. The surface area of the collectors varies depending on the users' water needs. It is typically around 4 square meters for a single household to cover hot water needs and may reach up to 20 square meters when also used for home heating. This area also depends on the solar radiation level in the region. The collectors are usually installed on a sloped roof to ensure maximum exposure to sunlight.
- ✓ Storage Unit: Also known as the solar storage tank or reservoir, this well-insulated unit keeps the water warm until it is used. Heat transfer is achieved through an internal heat exchanger. The tank is also equipped with an auxiliary heater powered by electricity, which is used in areas with low solar radiation.
- ✓ Transfer Unit: The transfer unit consists of all the components needed to efficiently move heat from the solar collectors to the storage tank. It includes a pump to circulate the heat transfer fluid, a set of temperature sensors, and a control system that activates the pump when necessary.[6]

#### **I.4 SOLAR COLLECTOR**

Solar energy collectors are a unique type of heat exchanger that converts the energy from sun radiation into the transport medium's internal energy. The primary element of the solar collector is any solar system [7]

There are two main types of solar collectors:

- Photovoltaic solar collectors
- ✤ Solar thermal collector

#### **I.5 Energy Storage Systems**

The idea of "energy storage" is to provide flexibility and improve confidence in energy systems. This involves adjusting energy supply and demand over time. To store energy, it is necessary first to convert it into a form that can be kept, and then to reconvert it for use as required.[8]

#### I.5.1 Techniques of energy storage [9]



Figure I. 5. Classification of major energy storage systems. [9]

**I.5.1.1 Mechanical energy storage (MES)** systems store energy by interconverting mechanical and electrical energy forms. During off-peak hours, excess electrical energy is converted into stored mechanical energy either as potential energy or kinetic energy. During peak demand, the stored mechanical energy is converted into electrical energy. As shown in (Figure I. 5), mechanical energy systems are categorized into four main types: PHES, GES, GES, CAES, and FES (in flywheel systems), where the first three types are based on storing potential energy and FES using kinetic energy. The main advantage of PHES systems is their ability to convert and discharge energy quickly, enabling efficient grid stabilization.



Figure I. 6. Classification of mechanical energy storage systems. [9]

#### I.5.1.2 Chemical energy storage

Systems are particularly well-suited for long-term energy storage, where energy is retained within the chemical bonds of atomic and molecular structures. This stored energy is released through chemical reactions that involve the breaking of original chemical bonds and the formation of new ones, resulting in a transformation of material composition. Currently, chemical fuels maintain global dominance in both the electricity generation and transportation sectors. Common chemical energy carriers include coal, gasoline, diesel, natural gas, liquefied petroleum gas (LPG), propane, butane, ethanol, and hydrogen. In typical energy conversion processes, these chemical substances are first transformed into mechanical energy before being converted into electrical energy for power generation. Modern CES technologies primarily encompass hydrogen storage systems, synthetic natural gas storage, and solar fuel storage systems.

**I.5.1.3 Electrical energy storage (EES) system:** Without changing the electrical energy into other types of energy, the EES devices store energy in an electric field. Electrostatic and magnetic energy storage systems are the two categories into which EES systems are divided (Figure I.8). Both supercapacitors and capacitors are technologies that store energy electrostatically. One type of magnetic energy storage device is the superconducting magnetic energy storage (SMES)



Figure I.7. Classification of Electrical energy storage systems. [9]

#### I.5.1.4 Hybrid Energy Storage

In order to achieve the required performance, the HES system idea combines suitable elements from many ESSs. High power storage systems and high energy density storage systems are the two types of ESSs. Fast response systems, which produce energy at higher rates but for shorter periods of time, are usually high-power density systems. implying that they provide energy more quickly but for shorter durations. Conversely, high energy density systems can supply power for longer periods of time but frequently respond more slowly. Two complementary storage systems, one with a high energy density and the other with a high-power density,

#### **I.5.1.5** Thermal Energy Storage

Thermal energy can be kept by increasing or decreasing the temperature of a material, which changes its sensible heat, or by altering its phase, which changes its latent heat, or even by using both methods together. As new energy technologies are created, both forms of thermal energy storage are anticipated to be used more widely. Thermal energy storage, or TES, involves keeping high- or low-temperature energy for future use. Some examples include storing solar energy for heating at night, saving summer heat for use during winter,

using winter ice for cooling in the summer, and storing heat or cooling produced electrically during times of low demand to be used later when demand is higher. Unlike fossil fuels, solar energy is not always accessible. Even the need for cooling, which often matches the highest levels of solar radiation, can be present after dark. TES can play a significant role in balancing the differences between the availability of thermal energy and its demand [10].



Figure I.9. Classification of thermal energy storage systems. [9]

#### • Latent Heat Storage

Latent heat storage relies on the absorption or release of heat as the phase transition of the storage material changes. The storage capacity of a latent heat storage (LHS) system with PCM is calculated by.

$$\boldsymbol{Q} = \boldsymbol{m}\boldsymbol{a}_m \,\Delta \boldsymbol{h}_m + \int_i^m \boldsymbol{m} \boldsymbol{C}_p \,dT + \int_m^f \boldsymbol{m} \boldsymbol{C}_p \,dT = \boldsymbol{m} \left[ \boldsymbol{a}_m \,\Delta \boldsymbol{h}_m \boldsymbol{C}_{sp} \,T_m - T_i \boldsymbol{C}_{lp} T_f - T_m \right] \tag{I.1}$$

LHS systems are characterized by the benefits of higher power density. Thermochemical storage systems rely on the energy released or absorbed during the breaking and formation of molecular bonds during a reversible chemical reaction. The storage capacity of these systems is determined by three main factors: the amount of storage material, the enthalpy of reaction (the latent heat of reaction) and the chemical conversion ratio.[11]

$$Q=a_r m\Delta h_r \tag{I.2}$$



Figure I.10. Temperature-Energy diagram for heating and cooling of a substance. [9]

#### • Sensible Heat Storage

Refers to a thermal energy storage mechanism wherein energy is stored by altering the temperature of the storage medium. The quantity of stored thermal energy is directly proportional to the material's density, specific heat capacity, volume, and temperature differential. The key thermo-physical properties governing the performance of sensible heat storage materials include specific heat capacity, density, and thermal conductivity. [12]

According to the first law of thermodynamics, the amount of heat energy stored per unit mass of a material during an isobaric process can be expressed as follows:[13]

$$\boldsymbol{Q} = \Delta \boldsymbol{h} = \int_{T_i}^{T_f} \boldsymbol{C}_p dT \tag{I.3}$$

where:

 $\Delta h$ : represents the change in specific enthalpy of the storage medium (J Kg<sup>-1</sup>)  $T_{i,}T_{f}$ : denote the initial and final temperatures (K), respectively.

 $C_p$ : is the isobaric specific heat capacity (JKg<sup>-1</sup>K<sup>-1</sup>)

Assuming constant specific heat capacity, the thermal energy stored per unit mass can be expressed as the product of the average isobaric specific heat  $C_p$  and the temperature difference  $(T_f-T_i)$ :

$$\boldsymbol{Q} = \Delta h = C_p \ (T_f - T_i) \tag{I.4}$$

#### a) Liquid Media Storage

Water is an excellent storage medium at low temperatures due to its high specific heat, low cost, and widespread availability. However, its high vapor pressure at elevated temperatures necessitates expensive insulation and pressure-resistant containment systems. Water is typically used within a temperature range of 25–90 °C. Storage tanks are constructed from materials such as steel, aluminum, reinforced concrete, and fiberglass, with insulation provided by glass wool, mineral wool, or polyurethane. Tank capacities can range from a few hundred liters to several thousand cubic meters. Petroleum-based oils and molten salts are commonly proposed as alternatives to water, particularly for high-temperature applications. Although petroleum-based oils and molten salts exhibit lower heat capacities (25–40 %) that of water on a weight basis), their significantly reduced vapor pressure enables stable operation at elevated temperatures beyond 300 °C. However, petroleum oils face practical limitations, as their thermal stability and safety risks restrict their use to temperatures below 350 °C. Additionally, their relatively high cost compared to water-based systems may impact economic feasibility in large-scale applications.[14]

SM	T [°C]	Density, ρ [kg/m3]	TC,k [W/ (mK)]	SH, Cp [kJ/(kg K)]	Effusivity,e (Ws1/2/ (m2 K))
Water	0–100	1000	0.58	4.19	49.30
Ethanol	Up to 78	790	0.171	2.4	18.01
Butanol	Up to 118	809	0.167	2.4	18.01
Engine oïl	Up to 160	888	_	1.88	_

Table I.1: Thermal properties of selected heat storage materials commonly used in solar thermal systems.

#### **I.5 Phase Change Materials (PCM)**

Certain materials can store or release large amounts of energy due to their ability to melt and solidify at specific temperatures. These materials are known as PCMs (phase change materials) because they naturally undergo a phase change that allows them to store or release energy at a constant temperature. PCM has a significantly larger heat storage capacity than other heat storage materials—nearly 5–14 times more heat per unit volume. Since there isn't

a material that possesses all the qualities needed to be the perfect PCM, choosing one for a certain application should be based on a thorough analysis of the substances' characteristics. Another factor to consider is the easy availability of phase change materials (PCM), From the perspective of minimizing the overall cost of thermal energy storage, it should be considered that increasing the energy density of phase change materials leads to a reduction in the amount of storage needed for a given application. As a result, the space required for storage can be reduced, and the required amount of heat can be stored at a relatively lower cost [1].

#### I.6.1 Phase Change Material Selection

Thermal properties	<ul> <li>Fit in the range of phase change or temperature</li> <li>The latent heat in terms of volumetric capacity should be as large as possible</li> <li>Thermal conductivity must be sufficient to ensure heat transfer</li> </ul>
Physical	High density
properties	<ul> <li>Acceptable size to avoid packaging problems</li> </ul>
Kinetic	Lack of cooling effect
properties	<ul> <li>Crystallization rate sufficiency</li> </ul>
	<ul> <li>Long-term chemical stability</li> </ul>
	No toxicity
Chemical properties	<ul> <li>Good fire resistance in line with current building codes</li> </ul>
Other	Low-cost MCP
properties	It's ample and abundant
	<ul> <li>Low manufacturing costs and no environmental impact.</li> </ul>

#### I.6.2 Types Of Phase Change Material

#### **I.6.2.1 Organic Materials**

Phase change organic materials include a wide range of compounds with distinct thermal properties, making them suitable for highly efficient heat management applications. These materials are categorized into four main classes according to their chemical composition and molecular structure: Paraffins, polyethylene glycol (PEG), fatty acids, and sugar alcohols. Each of these classes of materials has unique properties that give them important advantages for storing, transferring, or dissipating thermal energy in a variety of applications.

- Paraffins
- They are widely used in thermal control of buildings and cooling of electronic devices.
- They are characterized by a stable melting point and little volume change.
- They have low thermal conductivity and are flammable (requiring improvements such as additives or encapsulation techniques).
- Non-paraffinic materials (e.g., fatty acids)
- provide similar properties to paraffins with the added advantage of biodegradability.
- Suitable for textile and packaging applications due to their environmental compatibility.
- Also suffer from low thermal conductivity and flammability (requiring similar treatments [15].

#### **I.6.2.2 Inorganic Materials**

Inorganic Phase Change Materials (PCMs) can be categorized into metallic PCMs and salt hydrates. These materials exhibit excellent thermal stability over numerous heating and cooling cycles.

Among inorganic PCMs, salt hydrates are particularly attractive due to their minimal volume changes during phase transitions, high thermal conductivity, low cost, high latent heat of fusion, and non-flammability. However, their practical application faces challenges such as poor nucleation (leading to supercooling), incongruent melting, and irreversible melting-freezing processes. These issues can be mitigated through mechanical stirring, thickening agents, or chemical additives.

On the other hand, metallic PCMs offer high latent heat and superior thermal conductivity compared to other PCMs. Nevertheless, their use is limited by excessive weight and corrosion problems when exposed to environmental conditions over extended periods [16].

#### I.6.2.3 Eutectic Mixtures

Mixtures consist of two or more components (organic-organic, organic-inorganic, or inorganic-inorganic combinations) that solidify either congruently or incongruently during crystallization, forming homogeneous or heterogeneous mixtures. During melting, these components liquefy simultaneously at the same temperature, with or without phase separation. Widely employed in thermal energy storage applications due to their ability to absorb and release substantial amounts of heat at constant temperatures, common examples include paraffin wax-stearic acid and stearic acid-myristic acid mixtures. However, research in this field remains limited, primarily due to insufficient data on their thermo-physical properties and the need for further studies to better understand their phase-change behavior and optimize their performance. These promising phase change materials (PCMs) require additional development for their effective utilization in advanced energy storage systems[17].

Table I.2: Comparative advantages and disadvantages of different PCM categori	es
(organic, inorganic, eutectic).	

PCM	Advanteges	Disadvantages
Category		
	-Avaible whith a wide temperature	-Low thermal conductivity
	range	and enthalpy
	-High Heat of fusion	-No sharp melting point
	-Low subcooling	-High volumetic change
Organics	-physically an chemically stable	during
	-compatible with many containers and	Phase transition
	building materials	-Unstable under high
	-Environmentally safe and non-	temperatures
	radiative	-Costly for pure materials
	-Stabile after many cycles	-Toxic (some Types)
	-Recyclable	
	-High thermal storage and good	-Considerable volumetric
	thermal conductivity	change during phase
Inorganics	-Avaible whith low cost	transition
	-Sharp melting temperature	-Show phase segregation and
	-Low vapour pressure	subcooling
		-uncompatible with meals
	-Sharp melting temperatures	-costly
Euterics	-High storage capacity	-Limited in building
		application

#### I.7 Conclusion

Solar energy storage is an urgent necessity to address many issues such as intermittency in sources such as solar energy (clouds and wind) and for use in systems that require constant heat because it is environmentally friendly and inexpensive, and the importance of food hydration in maintaining the quality of food products and providing a safer and quality product. Both energy storage and hydration have a purpose, the first improves the efficiency of industrial processes and reduces energy losses and the second focuses more on product quality, and their integration with can provide more sustainable and efficient solutions for the food industry.

### Chapter II : Artificial Neural Networks

#### **II.1** Biological Neural Networks

The neuron is the fundamental component of the central nervous system. The brain is made up of roughly one billion neurons, each of which has between 1000 and 10,000 synapses, or connections.

A neuron is a type of cell made up of a noyau and a cellular body. The cellular body ramifies to generate what are known as dendrites. There are so many that they are referred to as dendritic or arborization chevelure.

Figure II.1: The Information is transmitted from the outside to the neuron's soma, or body, by the dendrites. The neuron then transmits its information to other neurons via the unique axon. There is no direct transmission between two neurons. There is a gap between neurons of a few tens of angstroms between the axon and the dendrites. A synapse is the intersection of two neurons. Depending on the type of synapse, the activity of a neuron can either increase or decrease the activity of its neighboring neurons. Thus, excitatory or inhibitory synapses are used.

The formal neuron that we will study next is very similar to the biological neuron that we have just presented. Because of this, the terminology used in literature to describe a formal neuron is heavily influenced by biology.

Learning methods increasingly draw inspiration from biology through the mathematical formality of artificial neural networks [18].



Figure II.1: Structure of a biological neuron showing dendrites, nucleus (noyau), axon, and synapses.

#### **II.2** Artificial Neuron

Biological neural networks easily perform complex cognitive tasks such as pattern recognition, signal processing and learning by example, as well as higher cognitive functions like memorization and generalization. The hypothesis that intelligence emerges from the organization and interactions between elementary brain units has motivated the development of artificial neural networks (ANNs).

Structure of an Artificial Neuron as illustrated in (Figure II.2), an artificial neuron is an elementary computational unit characterized by:

- Weighted inputs: Each neuron receives several input signals, each associated with a coefficient w (weight, or synaptic weight), reflecting the importance of the connection.
- A summator (aggregation function): Combines the weighted inputs into a single value.
- A transfer function (activation function): Transforms the weighted sum into a nonlinear output signal.
- A single output: Transmitted to one or more downstream neurons via weighted connections.



Figure II.2 Structure of an artificial neuron showing weighted inputs, summation, activation, and output.

The processing performed by the elementary neuron can be represented mathematically by the following equations:[19]

$$y(k) = F(\sum_{i=0}^{m} w_i(k) \cdot x_i(k) + b)$$
(II.1)

Where:

- $x_i(k)$  is the input value in discrete time kwhere *i* goes from 0 tom
- $w_i(k)$  is a weight value in discrete time kwhere *i* goes from 0 tom,
- **b** is bias,
- **F** is a transfer function,
- y(k) Is output value in discrete time k.

#### **II.3** Neural Networks and Activation Functions

Neural Networks are a network of multiple layers of neurons consisting of nodes that are used for classification and prediction of data provided some data as input to the network. There is an input layer, or many hidden layers, and an output layer. All the layers have nodes, and each node has a weight that is considered while processing information from one layer to the next layer.



Figure II.3: Architecture of a multilayer perceptron (MLP) with input, hidden, and output layers[20].

If a neural network does not employ an activation function, the output signal would simply be a basic linear function, essentially a polynomial of degree one. While linear equations are straightforward to solve, their complexity is inherently limited, lacking the capability to learn and discern intricate patterns from data.

A neural network without activation functions behaves akin to a linear regression model, often exhibiting restricted performance and effectiveness. Ideally, a neural network should not only comprehend and compute linear functions but also handle more sophisticated tasks, such as modeling diverse data types like images, videos, audio, speech, and text. Hence, the utilization of activation functions and advanced techniques like deep learning is crucial, enabling neural networks to make sense of complex, high-dimensional, and nonlinear datasets, particularly those featuring multiple hidden layers [20].

#### **II.3.1** Types of Activation Functions

Net inputs are one of the most important components of a neural network. These inputs are processed and converted into outputs, referred to as unit activation, through a scalar-to- scalar function known as an activation function, threshold function, or transfer function. Among the different types of activation functions, squelch functions play an important role by restricting the output of a neuron within a predefined range. These functions ensure control over the amplitude of the signal by nonlinearly compressing the output to a finite value.

1. Binary Step Function	6. Leaky ReLU
2. Linear	7. Parametrized ReLU
3. Sigmoid	8. Exponential Linear Unit
4. Tanh	9. Swish
5. ReLU	10. SoftMax[20].

#### **II.4** Types of Artificial Neural Networks

#### **II.4.1 Single Layer Perceptron (SLP)**

The term 'simple unit' in neural network architecture denotes the fundamental neuron model, specifically referring to the (MP) neuron model or single-layer perceptron introduced by McCulloch and others in 1943 [14]. In this model, neurons first receive input signals that are multiplied by their corresponding connection weights. These weighted inputs are then summed and compared against the neuron's threshold value before being processed through an activation function to produce the final output, which subsequently serves as input to other neurons in subsequent layers. This computational sequence propagates through the network until reaching the output layer, with the complete process illustrated in (Figure II.4) [21]



Figure II.4 Mathematical representation of an artificial neuron using weighted sum and activation function. [21]

#### II.4.2 Multi-Layer Perceptron (MLP)

Multilayer perceptron networks (MLPs), also known as feedforward neural networks, are among the most widely used neural network architectures due to their versatility in solving diverse issues. MLPs operate under a supervised learning framework, where the network learns input-output relationships from labeled training data. These networks infer only basic patterns from the examples provided, which implicitly encode the necessary functional mappings.



Figure II.5: Deep neural network architecture illustrating input, multiple hidden, and output layers [22].

A multi-layer network consists of three basic layers: An input layer, one or more hidden layers, and an output layer, each consisting of nonlinear processing units (neurons). Information propagates unidirectionally from the input to the output layer via weighted connections that determine the strength and importance of the connections between neurons. These weights are essential for signal propagation and encapsulate the network's learned knowledge of the relationship between the issue and the solution. In environmental modeling,

for example, environmental variables (inputs) are processed to predict biological responses (target outputs), where hidden layers enable the network to capture non-linear relationships[22].

#### **II.4.3 CONVOLUTIONAL NEURAL NETWORKS (CNNS)**

Convolutional Neural Networks (CNNs) share fundamental similarities with traditional Artificial Neural Networks (ANNs), as both consist of self-optimizing neurons that learn through training. Each neuron receives inputs and performs computational operations (typically a dot product followed by a nonlinear activation function) - the foundational mechanism underlying most neural network architectures. Throughout the network's processing pipeline, from raw image input vectors to final class score outputs, the system maintains a unified scoring function determined by its weight parameters. The output layer incorporates class-specific loss functions, while remaining compatible with standard techniques and methodologies developed for conventional ANNs [23].



Figure II.6 Architecture of a Convolutional Neural Network (CNN) showing convolution, pooling, and fully connected layers [23].

#### **II.4.4 Recurrent Neural Networks (RNNs)**

Recurrent Neural Networks (RNNs) represent a class of deep learning models that employ supervised learning principles. As a member of the machine learning family, deep learning - also referred to as hierarchical learning or deep structured learning - distinguishes itself from classical machine learning approaches through its layered architecture and ability to handle complex neural networks, particularly for sequential data processing. Unlike deterministic traditional algorithms, RNNs operate through a chained computational structure that enables temporal persistence by maintaining a hidden state element. This state mechanism allows the network to process inputs sequentially while preserving information across extended periods, making RNNs particularly effective for time-series and sequential data analysis tasks [24].



Figure II.7 Recurrent Neural Network (RNN) architecture in compact and unfolded representations for sequential data processing [24].

#### **II.4.5 Restricted Boltzmann Machines (RBMs)**

Restricted Boltzmann Machines (RBMs) represent a two-layer generative stochastic artificial neural network architecture comprising a visible input layer and a hidden layer, without an output layer. The network exhibits full connectivity between all visible units and all hidden units, while prohibiting intra-layer connections between nodes within the same layer. This connection pattern classifies RBMs as symmetric bipartite graphs. The architectural constraint prohibiting same-layer neuron connections gives rise to the "restricted" designation in Boltzmann machines.

As energy-based models, RBMs derive from the broader class of Boltzmann machines, which themselves constitute a specialized variant of Hopfield networks based on Markov random field theory (Fig. 4). In the RBM architecture, each neuron performs computations and makes stochastic decisions regarding whether to transmit received inputs. The training of RBMs typically employs the contrastive divergence algorithm [25].



Figure II.8:Structure of a Restricted Boltzmann Machine (RBM) with visible and hidden units and full bipartite connectivity [25].

#### **II.4.6 Deep Belief Networks (DBNs)**

Deep learning, a subfield of machine learning, focuses on learning hierarchical representations through successive layers of increasing meaningfulness. This approach utilizes artificial neural networks (ANNs) - biologically-inspired algorithms that mimic the brain's structure and function. These multi-layered computational models automatically learn multiple levels of data abstraction, with architectures typically exceeding three neural layers (including input and output layers).

Figure II.9: The layered representations emerge through interconnected neural networks, organized in sequentially stacked layers. Model complexity scales with both the quantity of hidden layers and their neuronal density, enabling more sophisticated representations at the cost of increased computational resources. Figure II.9 illustrates the characteristic architecture of these deep learning systems [26].



Figure II.9: Comparison between a simple neural network and a deep learning neural network architecture [26].

ADVANTAGES	DISADVANTAGES
In traditional distributed systems, information is stored across the entire network rather than in a centralized database. Consequently, the loss of partial data in specific nodes does not disrupt the overall functionality of the network. Robustness to incomplete data: Once an artificial neural network (ANN) is trained, it can generate outputs even when presented with partial or incomplete input data. The extent of performance degradation in such cases depends on the significance of the missing information. Fault tolerance capability: The corruption of one or more neurons within an artificial neural	Hardware dependency: Due to their inherent parallel architecture, ANNs require specialized processing units capable of performing parallel computations. This makes their practical implementation conditional on the availability of a compatible computing architecture. The most significant issue with ANNs is their unexplained behavior. When an ANN generates a probing solution, it doesn't explain how or why. This diminishes network trust The absence of prescriptive design principles for artificial neural networks necessitates an empirical approach to architecture selection, typically involving extensive experimentation
network (ANN) does not preclude the network	and performance evaluation.
from producing an output. This inherent resilience ensures robust fault tolerance in ANN architectures.	
Distributed memory architecture: For an	
artificial neural network (ANN) to learn effectively, it must be trained using	Numerical encoding requirement: ANNs' exclusive processing of numerical inputs
adjusting its parameters based on the desired outputs. The performance of the network is highly dependent on the quality and comprehensiveness of the training data. If the training set fails to adequately represent all possible variations of the input space, the network may generate erroneous outputs	necessitates careful problem formulation through feature engineering. The quality of this data transformation, which strongly governs network efficacy, is inherently tied to the operator's domain knowledge and technical skill
Progressive performance degradation: The network exhibits gradual deterioration in operational efficiency rather than immediate failure. This incremental decline results in progressively slower performance over time without sudden functional collapse	Indeterminate training duration: The training process terminates when the network achieves a predefined error threshold on the training set. However, this stopping criterion does not guarantee optimal model performance, as it may represent either premature convergence or suboptimal local minima.

#### Table II .1: Advantages and Disadvantages of Artificial Neural Networks (ANNs)

### Chapter III : Material and Method

## Chapter IV : Result and Discussion

# General Conclusion

#### **General Conclusion**

This research successfully demonstrated the viability and efficiency of using a solar water heater for rehydrating dates under the real climatic conditions of Ghardaïa. The results confirmed that operational temperatures between 39°C and 50°C were optimal for achieving desirable physical transformations in the dates—such as color and texture improvements— without undesirable phenomena like foaming or off-flavors. Although higher temperatures accelerated the rehydration process, they also posed risks of sugar leaching and damage to the cellular structure, underscoring the need for precise temperature control.

The study further highlighted the influence of varietal characteristics, such as the presence of a waxy surface layer, which significantly affected hydration kinetics and water absorption rates. This finding emphasizes the importance of tailoring rehydration strategies to specific date varieties to maximize quality and efficiency.

Mathematical modeling using Peleg, Weibull, and exponential models proved highly effective in describing the rehydration kinetics, with consistently high R<sup>2</sup> values confirming the reliability and robustness of these models. The analysis of effective diffusion coefficients revealed a strong dependence on temperature, reflecting the interplay between water viscosity, molecular mobility, and absorption dynamics. These insights are crucial for optimizing process parameters to ensure consistent and high-quality rehydration outcomes.

The development and validation of the artificial neural network (ANN) model marked a significant advancement in process monitoring. With an  $R^2$  value of 0.968 and low error metrics (RMSE = 4.988), the ANN model accurately predicted the water temperature inside the solar heater based on real-time meteorological parameters. This capability demonstrates the potential of ANN models for real-time process control, enhancing the adaptability and efficiency of solar-based rehydration systems.

Overall, this work contributes both to the scientific understanding of date rehydration kinetics and to the development of sustainable, solar-powered postharvest technologies that are wellsuited to arid regions.

#### **Perspectives and Recommendations**

Building on the insights gained from this study, several avenues for future research and development are recommended:

- ✓ Prototype Optimization: Enhance the design of the solar water heater by improving insulation, integrating thermal storage, and optimizing heat distribution to achieve more uniform temperatures and reduce losses.
- ✓ Varietal Studies: Expand the scope of the study to include additional date varieties with different physicochemical properties, particularly focusing on the role of surface waxes, sugars, and fiber content in rehydration behavior.
- ✓ Hybrid Systems: Investigate the integration of solar energy with auxiliary heating systems (such as biomass or electric heaters) to maintain consistent rehydration temperatures during cloudy conditions or at night, ensuring year-round operation.
- ✓ Real-Time ANN Deployment: Implement the ANN model in an automated control system to dynamically regulate water temperature and process parameters based on live weather data, enhancing process reliability and efficiency.
- ✓ Product Quality Assessment: Conduct comprehensive sensory and nutritional analyses to evaluate the effects of rehydration temperature and process duration on taste, texture, sugar content, and overall product acceptability.
- ✓ Techno-Economic and Environmental Analysis: Perform a detailed assessment of the economic feasibility, energy savings, and environmental benefits of using solar water heaters for large-scale date rehydration. This analysis will support the development of business models for local farmers and cooperatives, encouraging wider adoption.

Through these recommended research directions, the sustainable processing of dates can be significantly improved, leading to higher product quality, reduced energy consumption, and enhanced socioeconomic resilience for communities in arid regions. This aligns with broader goals of sustainable agriculture and climate-resilient food systems.

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